A FRAMEWORK ON AUTOMATIC RFID TAG DETECTION

A thesis submitted in partial fulfilment of the requirement for the degree of

Master of Technology

In

Electronics and Communication Engineering

Specialization: Electronics and Instrumentation

By

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National Institute of Technology Rourkela

Rourkela, Odisha, 769008, India

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Under the Guidance of

Dr. Samit Ari

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May 2015

DEPARTMENT OF ELECTRONICS AND COMMUNICATION ENGINEERING, NATIONAL INSTITUTE OF TECHNOLOGY, ROURKELA, ODISHA -769008.

CERTIFICATE

This is to certify that the work done in the thesis entitled **A Frame Work on Automatic RFID Tag Detection** by **Ailla Goutham kumar** is a record of an original research work carried out by him in National Institute of Technology, Rourkela under my supervision and guidance during 2014-2015 in partial fulfilment for the award of the degree in Master of Technology in Electronics and Communication Engineering (Electronics and Instrumentation), National Institute of Technology, Rourkela.

Place: NIT Rourkela

Date:01-06-2015

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DECLARATION

I certify that,

a. The work presented in this thesis is an original content of the research done by myself under the general supervision of my supervisor.

b. The project work or any part of it has not been submitted to any other institute for any degree or diploma.

c. I have followed the guidelines prescribed by the Institute in writing my thesis.

d. I have given due credit to the materials (data, theoretical analysis and text) used by me from other sources by citing them wherever I used them and given their details in the references.

e. I have given due credit to the sources (written material) used by quoting them where I used them and have cited those sources. Also their details are mentioned in the references.

A.Goutham Kumar

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ABSTRACT

RFID technology is the well developed technology. Which is having so many applications in real life. But along with large number of applications it is also having some disadvantages. Like this technology fails with cartons containing metal, water or any liquid content. This is due to absorption of radio waves by liquid content. Along with this there is one more problem which is low detection rate. RFID Detection is nothing but successful identification of rfid tag. Using high signal strength reader we can increase the detection rate but it is up to small level. For better improvement we are going for intelligent method. [1]

Detecting of RFID transponder with help of RFID reader is most significant in the radio frequency identification systems [2]. For development of RFID technology successful tag detection is compulsory. The major considerations effecting the successful tag detection by RFID interrogator contain transponder position and relative position of the interrogator and reader field area [1][27]. In this project we examine the features of tag identification on the two dimensional plane by an experiment approach depending on the received signal strength from the tag. We perform a process for calculating identification linked directly to the strength of transponder with help of artificial neural networks and Support vector machine.

The main advantage of this method is to prevent time consumption and decrease the price by immediate detection of transponder [3] [4] [5] [1]. No human intervention is required [2]. Many experiments revealed that the method can forecast the transponder recognition with an accuracy of 94% for different reader antenna positions. This method is mainly helpful in finding out the best transponder identification changing feature conditions. [1] [2] [3][27].

CONTENTS

LIST OF FIGURES

LIST OF TABLES

CHAPTER 1

INTRODUCTION

1.1. Introduction

Radio Frequency identification is a branch of wireless communication uses radio waves for communication. RFID uses electromagnetic fields to transfer data for tracking and identifying of movable or non-movable objects [2]. RFID structure consists of an interrogator and RFID tag, application software and computer system. Using a particular device which contains antenna and integrated chip called RFID interrogator RFID technology track the information as they move from one location to other [1][18].

RFID reader is connected to the RFID device used for connecting with the tags with wireless & wired communication. Obtaining data from a transponder with help of an interrogator is depends on different factors of the RFID environment such as the category, place, and focus of the tag and distance between the transponder and interrogator [1][18]. The place and direction of tag are two vital features defining the successful rate in understanding RFID transponder files [1].

An RFID transponder is a small integrated circuit manufactured for transmitting information wirelessly [32]. An RFID transponder contains an exclusive identity in the form of binary code and other information which helps reader to read and then transmit to the databank (DB) server [2] [6] [7] [8]. The successful identification of RFID transponder by RFID interrogator is called “RFID tag detection” [30] [6].

1.2. Motivation

The main difficult related with the development of the RFID systems in an operational location is that RFID readers are unable to identify and read the information present in the tag [32]. This problem can be solved by finding by finding the best conditions and reasons giving the best tag detection should be identified and implemented before RFID system is used.

The analysis mentioned above is time consuming method. The problem can be solved by trial and error method which called as an experimental method. [31][33] In small areas trial and error can be implemented but in go downs and large industries this trial and error method is difficult implement. The detection rate is a main factor for advancement of the RFID systems before they can be broadly used in practice. [33][32] These difficulties are encouraged and motivated to perform research and experimental investigation.

1.3. Objective

In this research, I am focusing on getting data from RFID setup by performing experiments. Same data is used to train a neural network and obtain the signal strengths at different positions with intelligent method.

With this intelligent method we can find the signal strength at all different positions, knowing this strength we can easily use the tags and readers in high signal strength areas, by which we can increase the rate of tag detectability. For this proposed method, initially we made a setup to calculate the signal strength at different positions, and using MAT Lab the feed forward neural network is designed. Using signal strength obtained from experimental setup the designed neural network is trained and appropriate weights of the neural networks are calculated. Using those weights signal strength at different positions can be calculated.

1.4. An overview of RFID technology

1.4.1. Introduction

Radiofrequcncy Identification(RFID) is a branch of wireless communication which uses radio waves for communication between its objects, tags and readers and for identification of RFID tags using readers. Fundamental components in RFID system are RFID tag, RFID Reader, Software, Data storage memory(Data Base) [2] [6] [7]. There are many types of RFID systems are available in this modren world which uses different radio frequencies for there communication. Based on these frequency range RFID systems are classified into three groups.

1.4.2. Types of RFID Frequencies:

Low Frequcncy Range: It uses the frequencies in the range of 125-148KHz. With this frequcncy range upto 3 feet range of communication is possible. This type of RFID systyem most commonly used for pet animals and car keylock tracking and identification [6].

High Frequency Range:It uses the frequency of 13.56MHz. communication range between reader and tag in this class of RFID System is more then 3feet. Most common application of this class are in the field of library for book identification, clothing identification, in usage of smart cards. This frequency has one advantage i.e. it is not affected by interference coming from water and metals [6].

Ultra High Frequency Range: It uses the frequencies in the range of 850MHz-950MHz. Range of communication is very good in this class and it is upto 25feet. This range of RFID System offers high reading speeds i.e. it can read many tags at a time and tags per second is also high. Applications in these range frequencies are in supply chain tracking, for tracking boxes,pallet,container,trailer tracking [6] [9].

1.4.3. Basic components of an RFID system

- **RFID Tags**

In RFID system tags are one the basic elements [6], which are attached to the items to be tracked. Tags are made up of integrated chip and contains antenna, memory. Antenna is used for doing communication with reader, and memory is used to store the unique identification information, source and destination addresses along with useful data so that it can be read and tracked by RFID interrogators anywhere [9][30]. Tags are classified as Passive tags and Active tags. Passive tags are inexpensive, tinier, immeasurable life span [8] because they never consume power. Reading limit is 10cm to a few meters. Active tags are having a reading range around 100 meters [9], but they consume power and thus life span is short and also price is high. However, active tags can survive for temperature, humidity and brightness so can be used in industries purposes [7].

Properties of Passive Tags [6] [10]**:**

- Don’t require power for operation, uses the power of reader.
- Storage capacity of passive tags is less it is up to 1KB.
- Read range of passive tags is shorter it is from 4 feet to 15 feet.
- Passive tags are mostly read only type tags.
- Cost of passive tags is less.

Properties of active tags [10] [7] [6]

- These tags are powered with battery.
- Storage capacity of these tags is longer up to 300feet.
- Active tags can be reusable i.e. can be re written by RFID readers.
- Cost is high compared with Passive tags.

- **RFID reader**

RFID reader is mainly accumulation of RFID antenna and Integrated circuit. RFID reader is used to make connection between the RFID tag and Software that controlling RFID operation. RFID Reader is also known as Interrogator [6] [7]. The reader communicates with the tag and do all the operation assigned to it like, getting the information scanning the card and reading the data present in the tag and writing into tag [6][48]. Using the reader antenna, data present in tag is captured. The collected information is passed to the computer or data base for processing.

- **Reader Antenna**

RFID Antenna is a part of RFID reader. RFID reader along with RFID antenna are used to collect the information present in the tag. Reader antenna is used to convert the electronic signal into electromagnetic signal and the converted signal is radiated into space. Radiated electromagnetic signal is collected by tags [1] [10][48].

- **Application Software**

Reader control software also known middleware is used to connect RFID reader with the application that they support. Software sends commands to the reader and collect the tag information from the RFID reader [6] [8][27].

These are the four basic elements of RFID technology. In which RFID tag ,reader and antenna can be seen. Application software is used for performing specific tasks. RFID reader and RFID antenna are connected with wired comminication. In between reader antenna and tag there is wireless communication. Tronsponder and antenna are communicated with radio waves [2][27][48]. Antenna is connected to reader and reader is connected to computer. Computer is stored with application specific software for performing specific tasks.

Below Figure:1 gives the fundamental elements of RFID System and how they are connected and communication takes place between them[42].

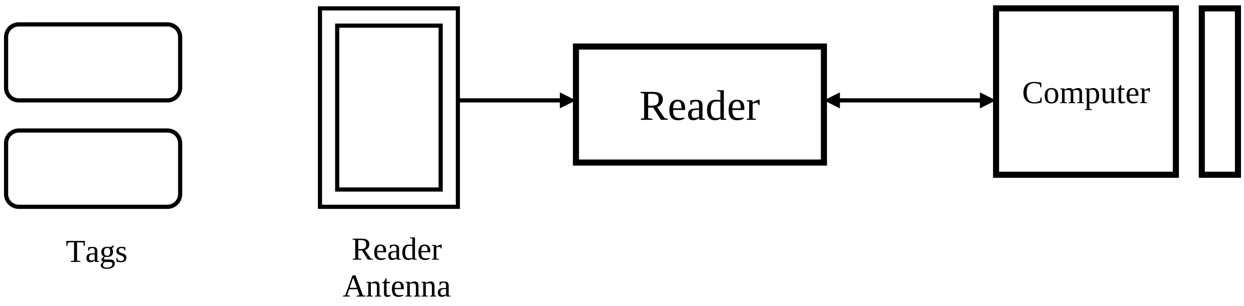

Figure 1: RFID System

1.4.4. Advantages of RFID System

RFID offers many advantages compared to manual systems and bar codes. Tags can be read if we pass near to it without physical contact. Unlike barcode RFID tags can be read if it is placed inside the box, container or any case. RFID Reader can read hundreds of tags at a time [9][6][30].

- Special position, line of sight is not required for reading.
- Reading and writing into tag takes less time and multiple tags can be read at a time.
- Information from movable objects can be read without interference.
- Each tag can carry a lot of data about 2Mb.
- RFID System can be combined with barcode technology [7].

1.4.5. Disadvantages of RFID System [6]

- Tag size is larger than barcode labels.
- RFID Tags are application specific.
- Detection Rate of RFID system is less.

- RFID Tag detection effects with the water and metal contents.[31]

1.4.6. Security and privacy issues of RFID [11]

Successful development RFID technology can create many new problems in this new modern world. Every user now a days is carrying many RFID Tags like cash cards, ID cards, car keys, medical cards and retail shops discount cards. From any of these, RFID Tag user's information can be captured by unauthorised persons. Eavesdroppers can listen to the transactions happening on the RFID Tag [28]. We can say that eavesdropper can have more chance of capturing information then the authorised persons. Since eavesdropper will use advanced technology and costly readers which support several hundred meters of range of area then authorised readers who can only read signals of tags within its limited range [28].

To solve these problems we have some techniques to improve our privacy in the field of RFID Technology.

- **Killing tags** [11]: some RFID tags have a facility of killing and reactivating by sending 8bit code from reader. While coming out of working place or store they can be killed, so that the tag fails working till reactivating.
- **Shielding tags** [11]**:** Tags can be shielded, i.e. placing in placing the tags in some containers like strictures made from metal or mesh, these containers will help in protecting tags from unauthorised persons by interference method.
- **Locking tags** [11]**:** It is same of Killing method, but instead of killing the tag a simple coding system is developed with which tags are get locked while coming out of work place are shops. These can be unlocked only after matching with the password given to the individual user.
- Regulating tags [11][28].
- Selective blocking tags [11][28]

1.4.7. Applications of RFID System.

- RFID System is used for tracking of goods and pet animals in the residences.
- Toll collections on highways and contactless payments.
- Airport luggage tracking and logistics.
- Accessing items in the ware house.
- RFID system in used in telemedicine applications, which uses wireless along with wired communication for providing medical services and information[43][8][6].
- In the field of location tracking like traffic movement control and parking management. Helps in monitoring wild life and livestock monitoring and tracking [8] [6][7].

CHAPTER 2

DATA ACQUISITION AND CLASS REPRESENTATION

2.1. Introduction

In this chapter it is explained about the procedure of the experimental performance, and the setup used for doing this experiment. In this section it is explained about how the data is collected at different positions. To perform this experiment we made a setup with the help of RFID Reader, RFID Tag and 10 ×10 cm square box and CRO with connecting wires. Main aim of this project is to improve the detection rate [1]. This is done with the help of support vector machines and neural networks.

Steps of experimental procedure.

1. Collect the signal strength at different tag positions. Note down the positions and signal strength, this is training data.
2. Train the artificial neural network and support vector machine with collected raw data, with the help of backpropagation algorithm adjust the weights of artificial neural networks.
3. Using those new weights, estimate the output signal strength at untrained tag positions.
4. Classify the estimated signal strength and find the prediction error with k fold algorithm

2.2. Experimental setup

For collecting the data I used RFID module for transmitting and receiving of radio waves and DSO to store the collected information in the form of wave forms and voltages. In the setup the RFID module is connected to the RFID antenna. Using ground and receive pins of antenna it is connected to the DSO with probe. There is wireless communication link between RFID tag and RFID reader antenna and wired communication between DSO and RFID module.10 × 10 grids are used for making the collection of data easy.

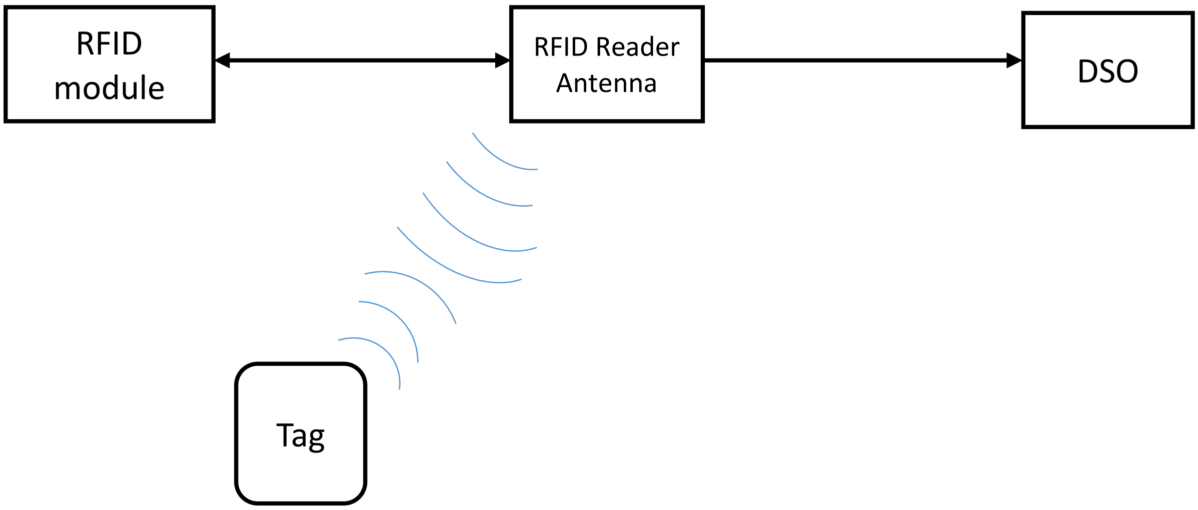

Figure 2: Experimental setup for data collection

2.3. Data collection

Square box is placed on table along with the RFID setup. Now it's time to find the signal strength at different position of tag on this square box. Calculating signal strength at each and every point of the square box is a tedious job. So we calculate the signal strength at intersections, 100 positions. And use that signal strength to estimate the strengths at other different positions. Square box is a 10 × 10cm box, divided into 100 grids each of 1cm^2 area. Using this square box we find the signal strengths at different positions on this square box.

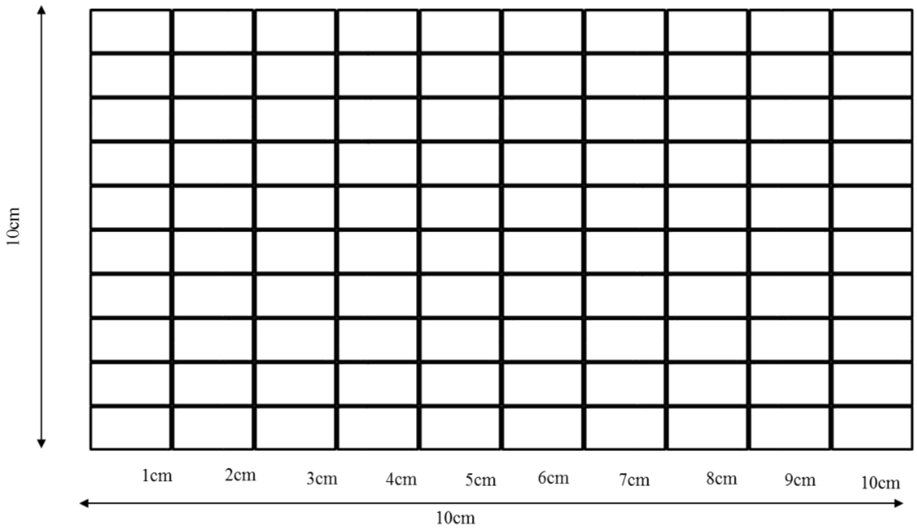

Figure 3: 10 × 10 Square box used in experiment for collecting data

In this experiment we are considered three cases of antenna positions by moving the antenna in horizontal positions. One case is placing antenna at 0 cm position, second one is placing at 5cm position and last case is keeping antenna at 10cm position of the x axis of the 10×10 square box respectively. With these three cases we found the signal strength at each and every position on the square box by shifting the position of tag in all directions.

First case of data collection (Antenna at (0, 0) cm position):

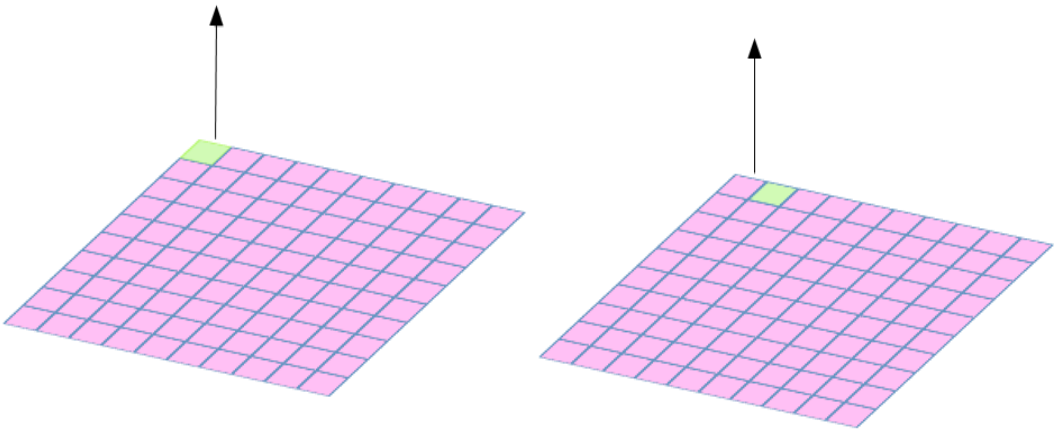

Figure 4: Setup for case1 antenna at (0, 0) position

Reader antenna is placed on one side of square box at 0cm position ant it is connected to DSO with the help of connecting wires and probes. Initially tag is placed at (1, 1) intersection. As soon as the setup is switched on RFID reader collects the signal coming from RFID Tag and it passes to the DSO.

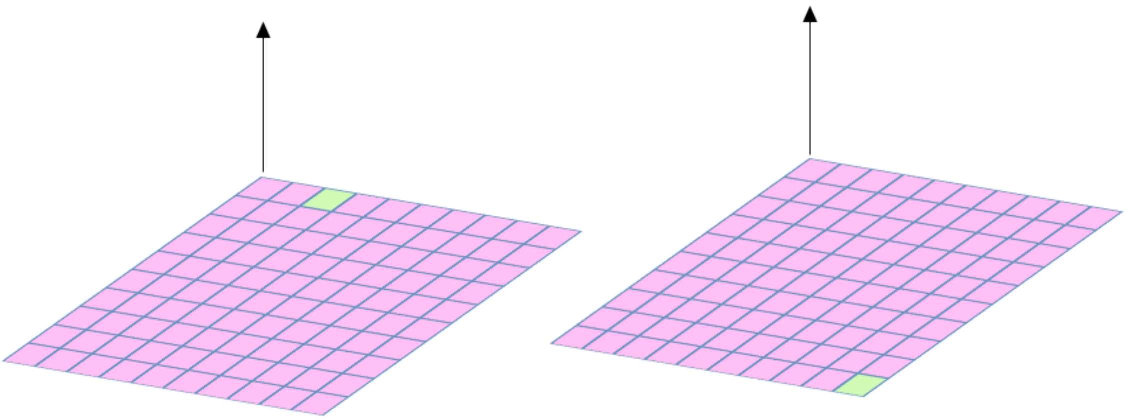

Figure 5: Setup for case1 antenna at (0, 0) position

DSO displays the reflected signal strength coming from RFID Tag on the monitor. This is the signal strength of tag at (1, 1) position. In the same way the signal strength t (1, 2), (1, 3)… (1,10), (2,1),(2,2)…(2,10)…(10,9), (10,10) are calculated. After doing all this experiment we get the reflected signal strength at all 100 intersection positons.

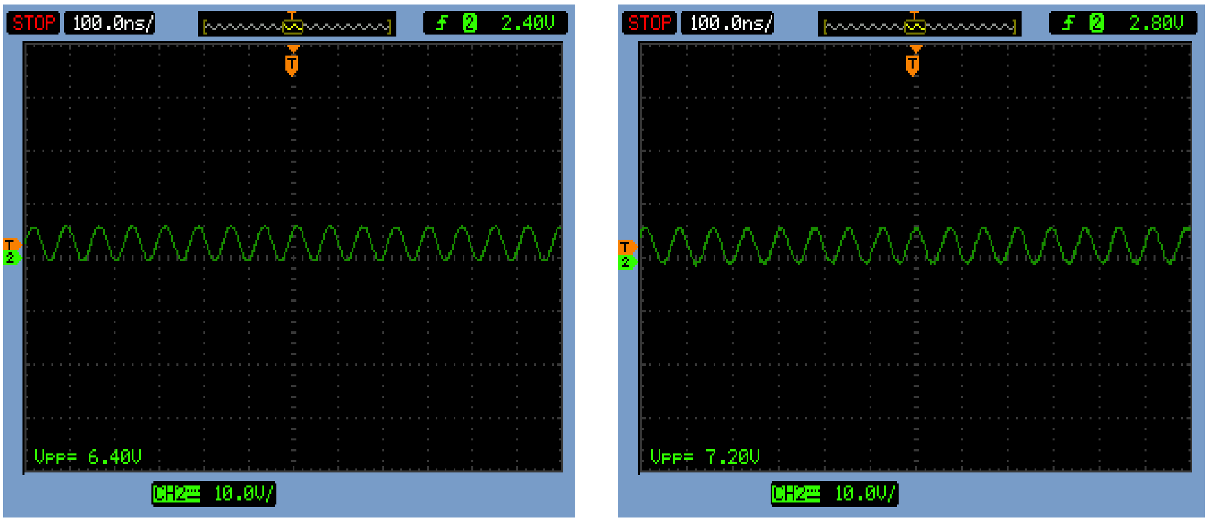

Figure 6: Signal strengths recorded in the DSO

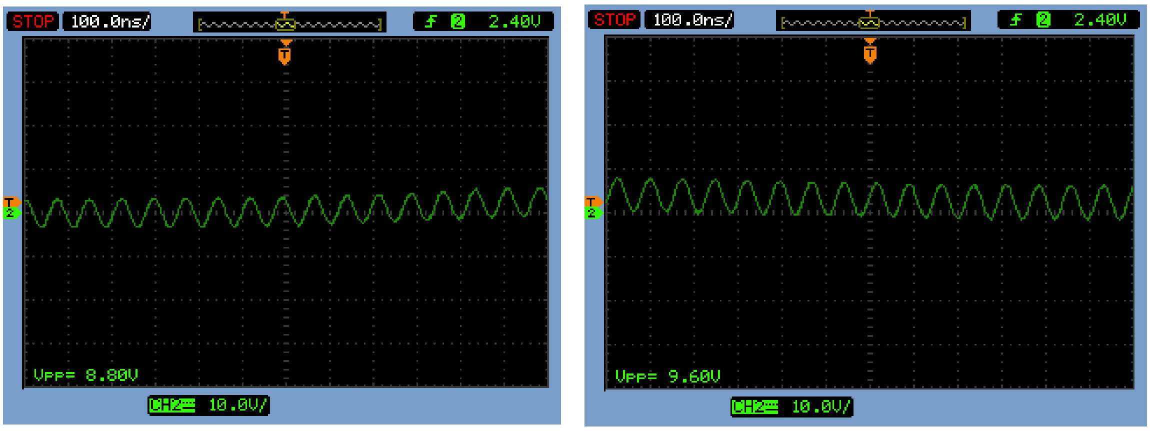

Figure 7: signal strengths recorded in the DSO

Above Figures 6 and 7 are the signal strengths recorded in digital storage oscilloscope. As the RFID tag moves away from the reader antenna signal strength varies propositionally to the tag positon.

In the same way the signal strength of RFID tag is calculated when the antenna is shifted to the positions (5, 0) and (10, 0) 5cm and 10cm away from the corner. Using this experimental data we can expect the signal strength of tag at every position when the antenna is placed at (5, 0) and (10, 0).

2.4. Collected data

The calculated signal strength of the three cases is given in the three tables. Tabular representation of the experimental data collected is given in below tables. Each table is having 10 columns and 10 rows. Each grid is giving the respective signal strengths when the rfid tag is place of the same grid of square box.

Table 1 is giving the data when antenna is placed at (0, 0) position of Square box used in the experiment. And table 2 is giving the strengths when antenna placed at (0, 5) and table 3 is giving results of antenna placing at (0, 10).

Table 1: Data collected in case1

	1	2	3	4	5	6	7	8	9	10
1	14.71	14.59	13.94	13.65	11.82	11.58	11.07	5.05	5.05	5.05
2	14.47	14.47	13.50	13.01	10.79	10.49	9.44	5.05	5.05	5.05
3	13.94	14.22	13.01	12.25	9.44	8.57	8.06	5.05	5.05	5.05
4	13.34	13.50	12.46	11.34	7.48	6.02	6.02	5.05	5.05	5.05
5	12.83	13.18	11.58	10.49	6.02	6.02	6.02	5.05	5.05	5.05
6	11.58	11.07	10.49	8.57	6.02	6.02	5.05	5.05	5.05	5.05
7	10.79	11.34	9.44	7.48	5.05	5.05	5.05	5.05	5.05	5.05
8	9.03	9.82	6.02	5.05	5.05	5.05	5.05	5.05	5.05	5.05
9	5.05	5.05	5.05	5.05	5.05	5.05	5.05	5.05	5.05	5.05
10	5.05	5.05	5.05	5.05	5.05	5.05	5.05	5.05	5.05	5.05

Table 2: Data collected in case 2

	1	2	3	4	5	6	7	8	9	10
1	5.05	5.05	5.05	10.49	11.34	12.25	13.65	13.94	14.71	14.59
2	5.05	5.05	5.05	9.44	10.17	10.79	13.18	13.50	14.22	14.35
3	5.05	5.05	5.05	8.06	8.57	10.17	12.25	13.18	13.94	14.08
4	5.05	5.05	5.05	6.02	6.81	8.57	10.79	12.25	13.50	13.34
5	5.05	5.05	5.05	6.02	6.02	6.81	9.82	11.58	12.83	13.01
6	5.05	5.05	5.05	5.05	5.05	6.02	8.06	10.49	11.07	11.82
7	5.05	5.05	5.05	5.05	5.05	5.05	6.81	9.82	10.49	11.07
8	5.05	5.05	5.05	5.05	5.05	5.05	5.05	6.02	7.48	8.06
9	5.05	5.05	5.05	5.05	5.05	5.05	5.05	5.05	5.05	5.05
10	5.05	5.05	5.05	5.05	5.05	5.05	5.05	5.05	5.05	5.05

Table 3: Data collected in case 3

	1	2	3	4	5	6	7	8	9	10
1	5.05	13.65	13.94	14.71	14.59	14.71	14.59	13.94	13.65	5.05
2	5.05	13.18	13.50	14.22	14.35	14.47	14.47	13.50	13.01	5.05
3	5.05	12.25	13.18	13.94	14.08	13.94	14.22	13.01	12.25	5.05
4	5.05	5.05	12.25	13.50	13.34	13.34	13.50	12.46	5.05	5.05
5	5.05	5.05	11.58	12.83	13.01	12.83	13.18	11.58	5.05	5.05
6	5.05	5.05	10.49	11.07	11.82	11.58	11.07	10.49	5.05	5.05
7	5.05	5.05	9.82	10.49	11.07	10.79	11.34	6.02	5.05	5.05
8	5.05	5.05	6.02	7.48	8.06	9.03	9.82	6.02	5.05	5.05
9	5.05	5.05	5.05	5.05	5.05	5.05	5.05	5.05	5.05	5.05
10	5.05	5.05	5.05	5.05	5.05	5.05	5.05	5.05	5.05	5.05

2.5. Classification of data:

The collected signal strength is converted in to dBm and classified into three classes based on the signal strength magnitude. Above 11M dB is named as Class A, from 8mdB to 10mdB signal strength is placed in Class B and Class C is from 5mdB to 7mdB.The classified data is used for training the support vector machine.

Table 4: classified data in case 1

	1	2	3	4	5	6	7	8	9	10
1	A	A	A	A	A	A	A	B	C	C
2	A	A	A	A	A	A	B	C	C	C
3	A	A	A	A	A	B	B	C	C	C
4	A	A	A	A	B	C	C	C	C	C
5	A	A	A	A	B	C	C	C	C	C
6	B	A	A	B	C	C	C	C	C	C
7	B	B	B	B	C	C	C	C	C	C
8	B	A	A	C	C	C	C	C	C	C
9	C	C	C	C	C	C	C	C	C	C
10	C	C	C	C	C	C	C	C	C	C

After classifying the signal as per the requirement the classified signal strength is arranged in the table as shown in these tables. Table 4 is the classification results of case 1 i.e. when antenna placed at 0cm position of square box.

Table 5: classified data in case 2

Positions	1	2	3	4	5	6	7	8	9	10
1	C	C	A	A	A	A	A	A	A	A
2	C	C	A	A	A	A	A	A	A	B
3	C	C	A	A	A	A	A	A	A	C
4	C	C	B	A	A	A	A	A	A	C
5	C	C	C	A	A	A	A	A	B	C
6	C	C	C	A	A	A	A	A	C	C
7	C	C	C	A	A	A	B	B	C	C
8	C	C	C	B	B	B	A	A	C	C
9	C	C	C	C	C	C	C	C	C	C
10	C	C	C	C	C	C	C	C	C	C

Above table5 is the classified signal strength for antenna placed at 5cm away position of square box.

Table 6: classified data in case 3

Positions	1	2	3	4	5	6	7	8	9	10
1	C	C	C	B	A	A	A	A	A	A
2	C	C	C	C	B	A	A	A	A	A
3	C	C	C	C	C	B	A	A	A	A
4	C	C	C	C	C	B	B	A	A	A
5	C	C	C	C	C	C	B	B	A	A
6	C	C	C	C	C	C	C	B	A	A
7	C	C	C	C	C	C	C	C	B	A
8	C	C	C	C	C	C	C	C	C	B
9	C	C	C	C	C	C	C	C	C	B
10	C	C	C	C	C	C	C	C	C	C

The tables 4, 5 and 6 above shows the signal strengths at different positions of tag according to antenna position. If we observe the classification tables it can be known that the signal strengths are distributed according to the position of antenna. Near the antenna the signal strengths are high and as we go away from the antenna the signal strength is goes on decreasing. Tag near antenna can be easily detectable but the tags away are not detectable. The places at which tags are not detectable can be known from finding the low signal strength areas. This can be find from designing an artificial neural networks which can find the signal strength using the position of the tag and antenna.

2.6. Conclusions

Experimental setup is arranged as per the need and using trial and error method the signal strength at multiples of 1cm position are calculated. Calculated signal strength is arranged in the form of tables. The calculated signal strength is distributed into three different classes as per the signal strength magnitude those classes are named as class A, B and class and these classified signal strengths are used for training of Neural Network and Support Vector Machine.

CHAPTER 3

ESTIMATING SIGNAL STRENGTH USING ARTIFICIAL NEURAL NETWORK

3.1. Introduction

Artificial neural network is a model invented to imitate the brain managing functions using the mathematical equations. Artificial neural networks are inspired from the brain structure and operation [5]. Similar to brain, artificial neural networks learn from examples. Initially ANNs experiences some tasks and implement them in the future. This process is called learning from training [4]. Artificial neural networks are application oriented i.e. each ANN has specific application and one can’t be used for other application. In brain we learn by adjusting synaptic weights of our neurons, in the same way neural networks will learn by updating weights [5].

Neural networks can be used in complicated or insufficient information areas and can be operated to capture the patterns and identify areas that are too complex to identify human and super computer systems [5] [12]. A skilled neural network can be called as specialist. Along with these there are many advantages with neural networks some of them are [5].

- Neural networks can learn from the training data or experiences.
- Neural network can organize the data it received during leaning time.
- Neural networks can be used in real time applications.
- Neural networks can identify the problems and can solve them.

Neural systems take an alternate way to deal with critical thinking than that of traditional PCs. Ordinary PCs utilize an algorithmic methodology i.e. the PC takes after an arrangement of directions so as to take care of an issue. Unless the particular steps that the PC needs to take after are known the PC can't tackle the issue. That limits the critical thinking capacity of traditional PCs to issues that we as of now comprehend and know how to tackle [13].

Basic element of artificial neural network

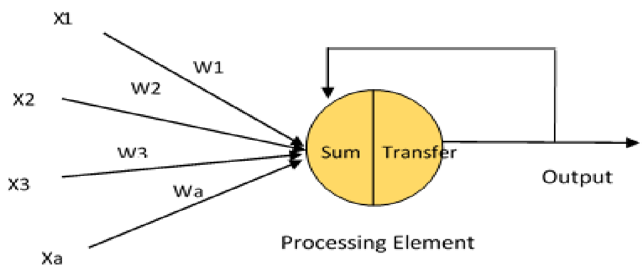

Figure 8: Artificial Neuron [5]

Basic element of artificial neural network is artificial neuron [5]. Artificial neuron is a device having many input and one output. Every neuron has to perform two operations, one is training. Second operation is to use the trained data to implement the new data operations. In implementation mode, using the training information the output of other new data is estimated. Output of a neuron is calculated using inputs and connection weights. Inputs are multiplied with weights and summed up to get the output, the sum calculated is given to a transfer function which limits the output as per the transfer function of activation function.

Although every ANN is constructed from basic building blocks of neurons, the arrangement of neurons will make difference in operations of ANNs. If neurons are connected in parallel form then it is called parallel neural network [5][26]. If the number of layers are changing the architecture and output of the neural network will also change. One of most popular inter connection model of artificial neural network is feed forward neural work [26]. In which data move from input to the output and as we move from input to the output the number of neuron decreases and number of layers increases [5]. Here we concentrate mainly on this feed forward neural network. Because in feed forward neural network calculating the output is easy and the architecture is also simple [23]. Everyone can easily understand the structure and output of the feed forward neural network. Weight updating of feed forward network is also simple with help of back propagation algorithm.

3.2. Feed Forward Neural Network

Neural network feed forward architecture is the well-known model of the artificial neural network. It is arranged in the form of layers. Input layer, middle layer and response layer [24] [14]. The structure of feed forward neural network is shown below.

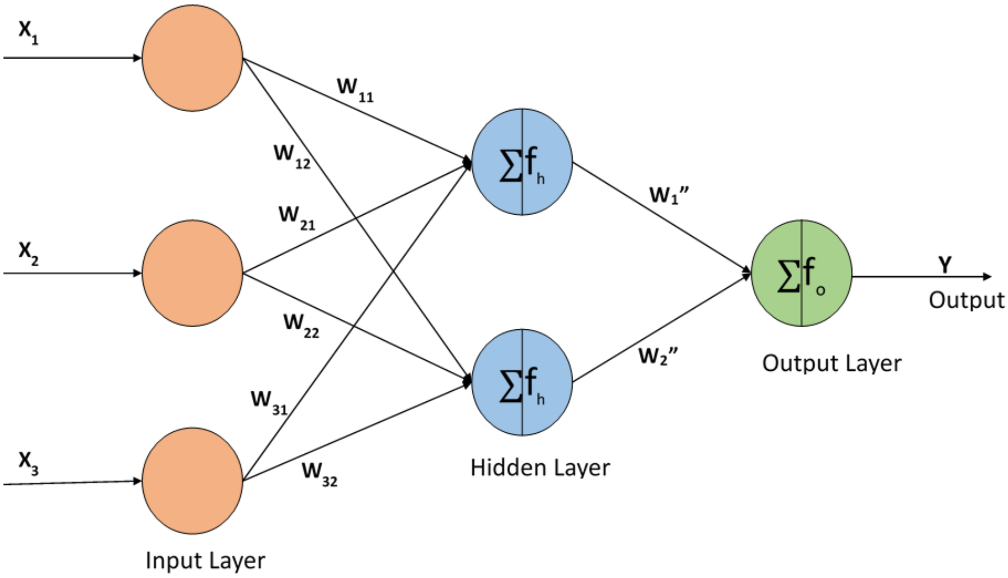

Figure 9: Feed Forward Neural Network

Data in this network flows from input side to output side via hidden layer so it is called as "feed forward" network. There are no loops and no cycles in this architecture of neural networks [14][24][45]. If we observe the feed forward neural network diagram it is having three data set points are going into input layer and which are multiplied with weights of neuron and have the output of three data sets which are given to the hidden layer. Output of hidden layer is connected to the input of output layer [13] [14][24]. Output layer is next connected to activation function. Activation function limits the output of the connected node. In this project I used the sigmoid function as activation function. Sigmoid function lies in between 0 and 1 but it never touches the 0 and 1 lines. Sigmoid function curve looks like English alphabet 'S'. A sigmoid function is having a positive derivative at each point [5][26].

3.3. Back Propagation Algorithm

In neural network area we are having so many network architectures, the backpropagation neural network model is the best one [5] [22] [23]. The network consists of feed forward architecture and it is trained through supervised learning technique.

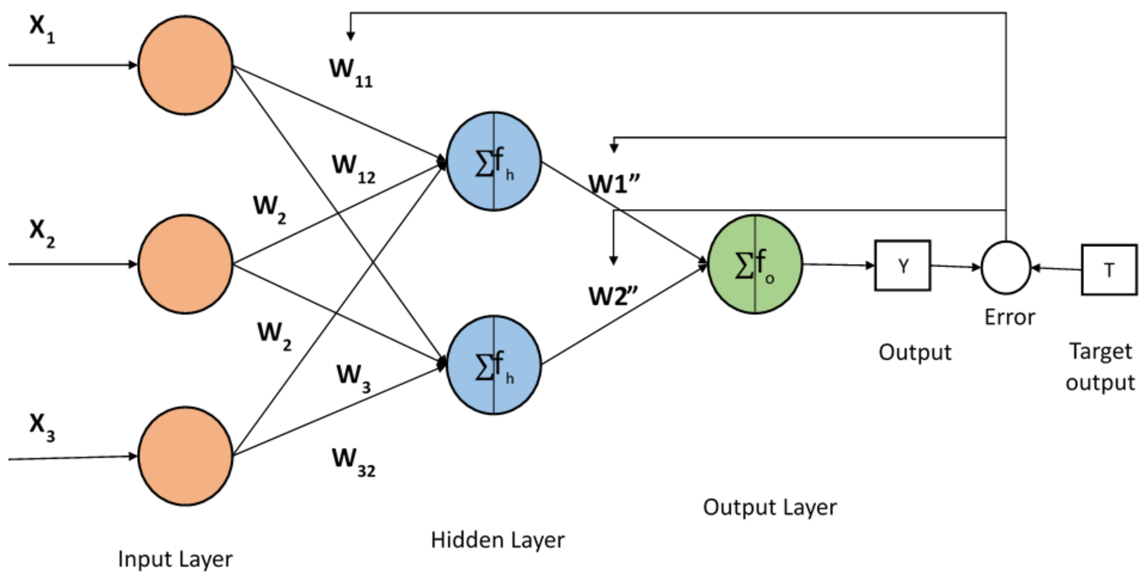

Figure 10: Back propagation algorithm

There are mainly two types of training techniques. [5] [46][47]

1. Supervised learning technique
2. Unsupervised learning technique.

In case of super vised learning we have both inputs and outputs. Using these input and output data sets the neural network is trained and the initial weights are changed based on the input output relationship. In case of unsupervised learning we are having only inputs. There is no need of output. If there are outputs also it neglects them and trains only with input data.[45][46][47]

The best among these two is supervised learning techniques, because it is like learning with master. If our weights divert or go into wrong direction i.e. instead of increase they may decrease or vice versa, then output data will guide us to the right way by checking the error. So in this projected we selected supervised training technique.

3.4. Training a Neural Network

The process of feeding data rules into neural network is called training. Every neural network will work only after training, just like a newly born child can understand the situations only after training and imitating. In the same way every neural network is to be trained, after training it can gain the knowledge, which can be used for classifying or estimating the new inputs.

Neural network trained by Back propagation consists of three layers and neuron interconnections. Each neuron interconnection is assigned some initial weights (w) through initial learning method. The output of neuron interconnection is weighted sum of inputs with weights. The final output is filtered by sigmoid transfer functions [5] [15] [12].

Back propagation neural network model uses three layers. Input layer, middle layer response layer. Before training the neural network some initial weights are fed to the neuron interconnections W_{11}, W_{12}… W_{33}. Using these weights the weighted sum of the input layer is given to the hidden layers, from hidden layer the weight sum is fed to output Y. This output is called predicted output. The predicted output is compared with the actual output and the difference between predicted and actual output is calculated, this is called error. Now here we have to minimise the error. So we can say that the learning process of backpropagation algorithm is an error minimization technique [5] [12]. This error can be minimised by adjusting weights according to error sign. With the help of updated weights predicted output of the second iteration is calculated, the output is compared with the actual output and weights are updated. The iterations are repeated until the limited error is found.

Consider in general the output of artificial neural network which consists of I inputs, H hidden layers, and one output which can be given as

$$F(X, W) = P[b_0 + \sum_{J=1}^{I} Q(X_J * W_H) * W_O] \tag{1}$$

F(X, W) is the output of the neural network.

P the activation function of neural network output layer.

Q is the activation function of neural network middle layer.

X_J= X=[X_1, X_2 …X_I] are Input data vector to neural network.

W_H= [W_{11}, W_{12}, W_{13}… W_{II}] are weights of input layer interconnection to hidden layer.

W_O= [W_1”, W_2”, W_3”, W_H”] are weights of hidden layer interconnection to output layer

The above shown equation gives the actual output. But it differs from desired output, and the difference between desired and actual output is known as error. The error has to be minimized.

This is done by backpropagation method since backpropagation uses the gradient descent method, one needs to calculate the derivative of the squared error function with respect to the weights of the network. Assuming one output neuron, the squared error function is [5]:

$$E = \tfrac{1}{2}(t - y)^2 \tag{2}$$

Where

E is the squared error.

t is the target output for a training sample.

y is the actual output of the output neuron.

New upgraded weight equation of the three layer neural network can be obtained by deriving the squared error function given in the above equation with respect to the weights.

In the same manner new weights of the three layer neural networks weights are updated. Using those new weights signal strengths at measured positions are calculated. The results of training and signal strengths at new positions are shown below in the form of table.

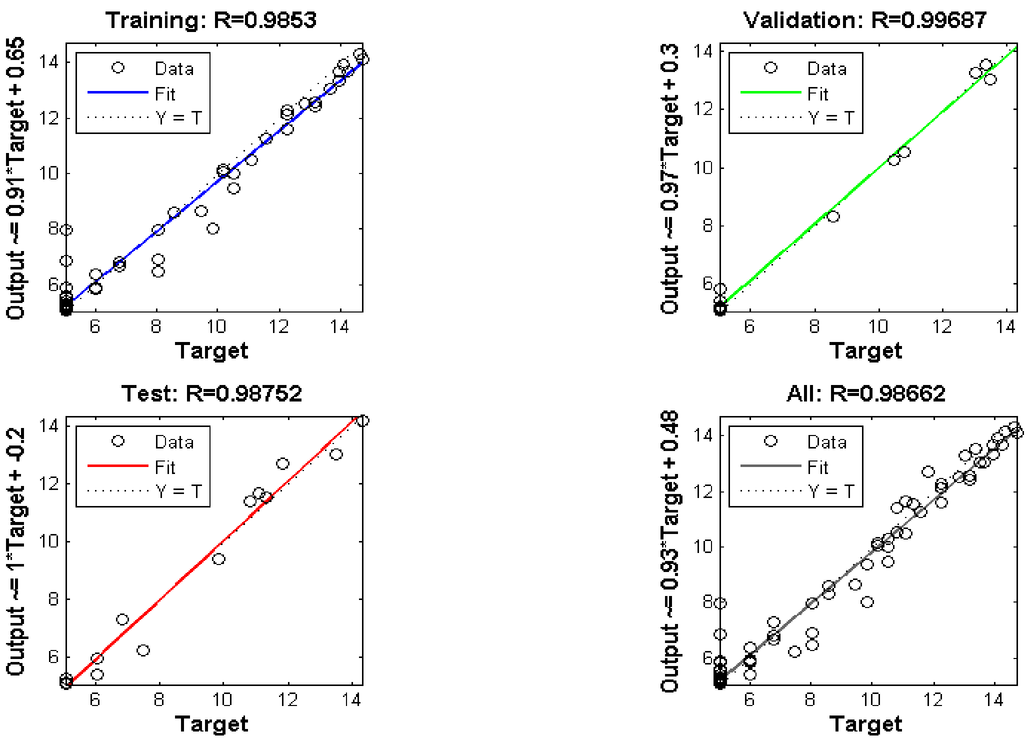

Figure 11: Results of Artificial Neural network Training

We first collected the training data using the experimental procedure explained in the previous chapter. Collected data is used for training of artificial feed forward backpropagation neural network. The above Figure: 11 shows the training results of the neural network. How accurately it is trained can be known from above shown results. While training, collected data is divide into two parts in the ratio of 70:30. 70% data is used for training and 30% data is used for testing the training results [15].

Blue colour line in results represent the error on training data. The dotted line shown is the zero error line. If we compare both dotted line with blue line there is no much deviation, it indicates that there is no error.

Green colour lines represents the validation error, training stops when validation error stops decreasing.

Red colour line is giving the error on 30% test data.

Fourth graph gives the combined results of training and testing data [15].

After training the neural network its weights are get updated [5]. Using the neural network tools in the MATLAB neural network model is trained and its respective weights are modified as per the required output values. After acquiring the updated weights the new data is given to the designed model. For that new data signal strength is calculated. In training we estimated the signal strength at multiple of 1cm positons and those signal strengths are given to the neural network for training.

Using those values now the signal strength at multiples of 0.5cm positions are estimated using neural network updated weights. Below tables are giving the results of signal strength at different positions when antenna at 0, 5, 10cm positon on the one of the edge of square box considered. Table 7 is giving the calculated signal strengths of 0.5 cm multiple positions when the antenna is placed at 0cm. If we observe the signal strengths it is known that high signal strength is accumulated near antenna at top left edge of the table given below. As we move away from antenna its signal strength get decreased. An in the column 9.5 the signal strength very low such that no tag can be detected in this area.

In table 8 it is given the signal strengths estimated when antenna placed at 5 cm position and varying the tag in position of 0.5cm multiple intersections. In this maximum signal strength is accumulated in the middle of the table. And table 9 gives the results obtained when third case data is given to the neural network. By this way signal strengths at unknown positions are estimated and tabulated in the below tables.

Table 7: Signal strengths calculated at unidentified region when antenna at 0cm

	0.5	1.5	2.5	3.5	4.5	5.5	6.5	7.5	8.5	9.5
0.5	14.70	14.70	14.60	14.23	12.70	11.72	11.51	8.01	5.05	5.05
1.5	14.68	14.59	14.14	13.68	12.20	11.22	10.97	7.86	5.05	5.05
2.5	14.51	14.10	13.52	13.15	11.36	9.93	9.49	6.90	5.05	5.05
3.5	13.66	13.48	13.06	12.49	10.00	7.71	7.04	5.78	5.05	5.05
4.5	12.54	13.24	12.70	11.54	8.40	6.21	5.77	5.33	5.05	5.05
5.5	10.36	12.29	11.73	10.42	7.73	5.89	5.54	5.20	5.05	5.05
6.5	8.49	10.74	10.26	9.15	7.06	5.44	5.11	5.05	5.05	5.05
7.5	8.35	11.90	11.30	7.51	5.15	5.05	5.05	5.05	5.05	5.05
8.5	5.72	5.90	5.14	5.06	5.05	5.05	5.05	5.05	5.05	5.05
9.5	5.05	5.05	5.05	5.05	5.05	5.05	5.05	5.05	5.05	5.05

Table 8: Signal strengths calculated at unidentified region when antenna at 5cm

	0.5	1.5	2.5	3.5	4.5	5.5	6.5	7.5	8.5	9.5
0.5	5.07	5.97	14.71	14.71	14.66	14.49	14.21	13.91	13.63	12.72
1.5	5.08	6.06	14.63	14.45	14.54	14.62	14.54	14.24	13.74	9.89
2.5	5.08	5.80	13.38	13.64	13.93	14.17	14.43	14.48	14.13	5.45
3.5	5.07	5.16	9.36	13.26	13.55	13.83	13.82	13.50	13.51	5.05
4.5	5.06	5.06	7.86	12.93	13.11	13.07	13.42	13.27	9.64	5.05
5.5	5.05	5.05	7.42	12.40	12.45	12.01	11.87	12.41	6.02	5.05
6.5	5.05	5.05	7.01	11.54	11.54	11.04	10.74	10.92	5.06	5.05
7.5	5.05	5.05	6.01	9.51	10.14	10.60	11.39	11.14	5.05	5.05
8.5	5.05	5.05	5.07	5.24	5.39	5.54	5.66	5.14	5.05	5.05
9.5	5.05	5.05	5.05	5.07	5.07	5.07	5.06	5.05	5.05	5.05

Table 9: Signal strengths calculated at unidentified region when antenna at 10cm

	0.5	1.5	2.5	3.5	4.5	5.5	6.5	7.5	8.5	9.5
0.5	5.51	6.12	7.32	9.23	11.36	13.01	13.94	14.39	14.58	14.66
1.5	5.28	5.59	6.28	7.61	9.60	11.70	13.22	14.05	14.43	14.60
2.5	5.16	5.31	5.67	6.46	7.92	9.98	12.02	13.41	14.14	14.47
3.5	5.10	5.18	5.36	5.77	6.66	8.24	10.36	12.31	13.57	14.22
4.5	5.08	5.11	5.20	5.41	5.88	6.88	8.59	10.74	12.59	13.72
5.5	5.06	5.08	5.12	5.22	5.46	6.01	7.13	8.95	11.10	12.84
6.5	5.06	5.06	5.08	5.13	5.25	5.53	6.16	7.40	9.32	11.45
7.5	5.05	5.06	5.07	5.09	5.15	5.28	5.61	6.32	7.69	9.70
8.5	5.05	5.05	5.06	5.07	5.10	5.16	5.32	5.70	6.51	8.00
9.5	5.05	5.05	5.06	5.06	5.07	5.10	5.18	5.37	5.80	6.71

3.5. Conclusions

In this chapter my aim is to find the signal strength at unknown positions. For this I took the help of neural networks, initially in neural networks some weights are assumed [5] and using the back propagation algorithm the three layer neural network is trained and after sufficient amount of iterations the weights are updated in the three layer neural networks. Those weights are used to find the unknown signal strengths, in this way at each and every position the signal strengths are calculated.

CHAPTER 4

CLASSIFICATION OF SIGNAL STRENGTH

USING SUPPORT VECTOR MACHINE

4.1. Introduction.

The support vector machine was is a branch of mathematics which derived from the statistics theory [16]. Support vector machine is a branch of machine learning, which uses supervised learning models for training the model. Support Vector Machine is mainly used for classification and regression applications [5][40] [41]. Support Vector Machine builds a hyperplane or a group of hyperplane in a large or unlimited dimensional space which is used for grouping and regression tasks. Good parting is attained by the hyperplane which has greatest margin distance from nearest training data points of any class, in general the greater the margin lower the error [1]. Neural network also performs the operation of classification and regression but the results of support vector machines are so accurate compared with neural network classification.

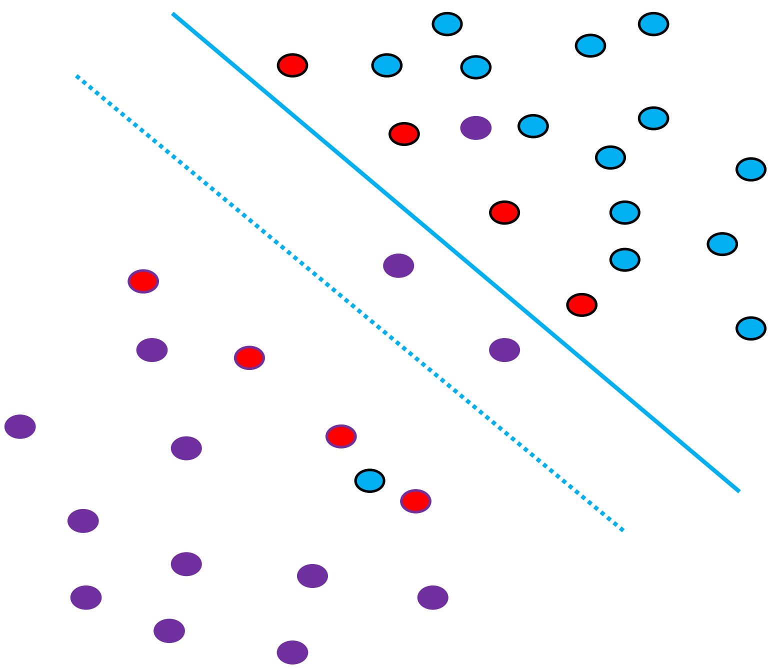

Figure 12: Separating plane near class 1

SVM Training procedure builds a model that allocates new examples into one category or other, using the training examples belongs to one of two categories [29] [34]. Support vector machine develops a model that separates the additional data in to two or more classes [29] [34].

SVM model is a demonstration of example training data in the space, the demonstrated data is categories and are divided by a clear gap which is as broad as possible [16]. New examples are then plotted into space and guessed to a category based on the side they drop on.

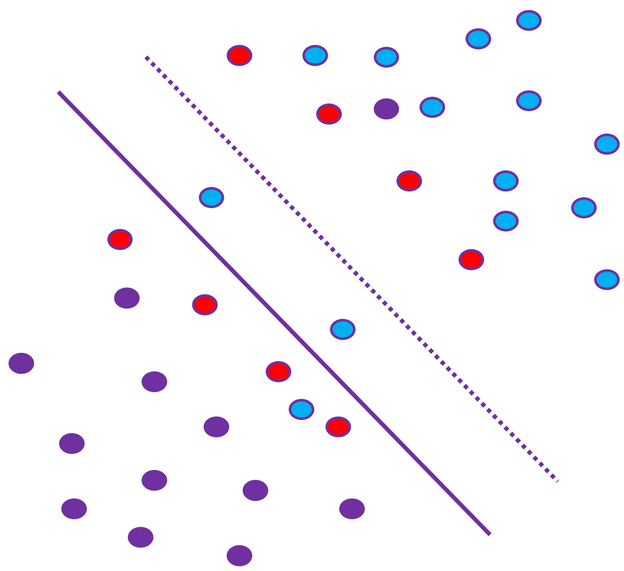

Figure 13: Separating plane partially near class2

Along with linear classification Support vector machines can classify nonlinear classification using kernel method, by mapping there inputs into higher dimensional feature spaces.

4.2. Linear classification.

Linear classification is also known as binary classification as in this case there are only two classes are present. The main idea of support vector machine is finding the best classifier or an N dimensional hyperplane that has maximum boundary and minimum error among the classes [34] [37] [38]. Here our task is to predict the best hyperplane that can divide test sample into one of the two classes accurately.

Let us consider one example training data in the form {Xi, Yi}, i=1, 2, 3…, Xi ϵ R^n be the input points and Yi ϵ{-1, 1}. We call {Xi} as input vector and Yi as the response variable. We also have Wϵ R^n & b ϵ R which are weight and bias respectively weight is a vector matrix [41]. If assume the considered example training data is linearly separable, i.e. we can draw a straight line f(x) =W^TX-b such way all the examples with Y_i= -1 come to class one and Yi= +1 come into other class [37] [44]. With this classification we can classify the new data according to the rule Y_{test}= sign (X_{test}).

For above training example classification we can have infinite hyper planes. How can we select the best hyper plane among all those possible hyper planes?[44] If we chose the plane which is close to the -1 class, while classifying, +1 class data will fall into -1 area as shown in Figure: 14and there arises a problem. Similarly if we chose the plane close to the +1 class, the data of -1 class fall into +1 as shown in Figure: 14.

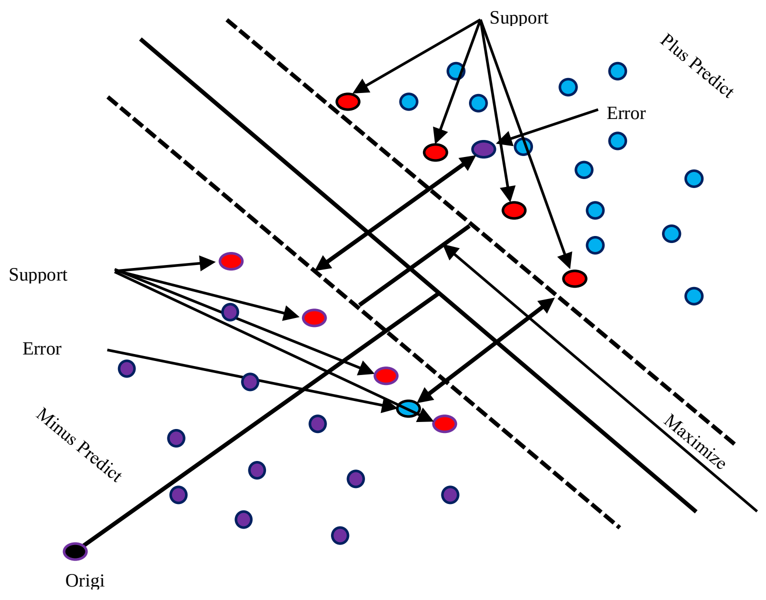

Figure 14: SVM Parameters

The separating hyperplane with these variables can be specified in terms and w and b as: {W.X} + b=0, where w is perpendicular to the hyperplane [5].

$$f(x) = w^T x + b = 0 \quad (3)$$

The above function gives the best hyperplane that separates the different classes.

If f (x_i) ≥0 the y_i is allocated to the positive class. (+1)

If f (x_i) <0 the y_i is allocated to the negative class. (-1)

From the Figure: 14 it is known that the length of normal line from origin to hyperplane is $\frac{\|b\|}{\|w\|}$, where $\|w\|$ is Euclidean normal of W. [5] The distance between plus side and minus side is $\frac{2}{\|w\|}$.

Data points which are lying near the plus plane and minus plane are called support vectors [5].

4.3. Non Liner Classification.

In case of nonlinear classification, the two classes are arranged in such a way that they can't be separable by linear boundary. In this type of nonlinear classification we take the help of kernel functions which are used to map data into higher dimensions [1][34][29], and then classifying using a linear boundary.

Consider the example shown in below Figure15:

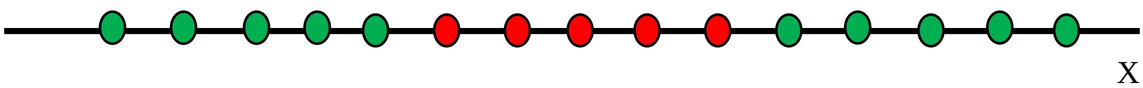

Figure 15: Example data in 1Dimension

Above Figure: 15 containing two classes of data. One type of class in the middle and other data class on both the ends of the one dimensional plane. If we observe them it is known that these two classes are not linearly separable. This type of data representation can be classified using mapping technique, which transforms the data into higher dimensions and then classifies using linear boundary.

If we map the example data in the Figure 15 in to two dimension as $X \rightarrow \{X, X^2\}$ [17][37]. Each example data now has two features derived from original feature. If we plot the data of those two derived features we got the Graph as shown in below Figure16.

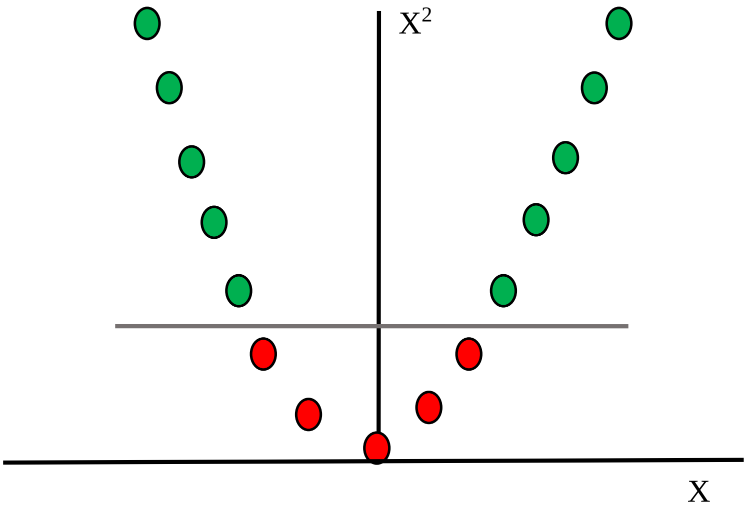

Figure 16: Example data Transformed into 2Dimension

The data is Nonlinear in old representation and it is linear for the new representation of two dimensional plane. If we see the two dimensional derived Figure16, now it is separated by a linear boundary line [18] [20]. By this way the nonlinear data is separated by using mapping technique.

Using mapping technique we can transform lower dimension data into higher dimension and can classify the data [1][35]. But there is a problem as we go to higher dimensions data.

If we have D dimension data represented as $\{X_1, X_2, X_3, X_4, X_5, X_{6\ldots}X_D\}$.

Let us consider feature mapping each feature uses two original features using quadratic mapping

$$\{X_1^2, X_2^2, X_3^2 \ldots X_1X_2, X_1X_3, X_1X_4 \ldots X_{D-1}X_D\}$$

Each new feature uses two original features.

In higher dimension cases computing feature mapping is a tedious job [5][20], representing the computed data is also very difficult. Sometimes it is inefficient to map higher dimension data.

In case of kernel trick there is no need of computing mapping explicitly [5]. Just by defining the kernel function we can transform into higher dimensions [22]. Computation with the mapped features remain efficient, by without computing also.

Let us consider two example P= $\{P_1, P_2\}$ and Q= $\{Q_1, Q_2\}$

Let suppose we have one kernel function K that uses the two inputs P and Z as

$$K(P, Q) = (P^TQ)^2$$

$$= (P_1Q_1+P_2Q_2)^2$$

$$= (P_1^2Q_1^2+P_2^2Q_2^2+2P_1P_2Q_1Q_2)$$

$$= (P_1^2, \sqrt{2}P_1P_2, P_2^2)^T (Q_1^2, \sqrt{2}Q_1Q_2, Q_2^2)$$

$$= \varphi(P)^T\varphi(Z)$$

The above K implicitly defines a mapping φ to a higher dimensional apace.

$$\varphi(P) = \{P_1^2, \sqrt{2}P_1P_2, P_2^2\}$$

Just by defining the kernel function we can map the data into higher dimensional plane without computing this mapping [5]. However if we compute mapping, it is a dot product of $\varphi(P)^T\varphi(Q)$ which is simple [18]. Computing same problem explicitly will be more expensive and difficult [5]. All the kernel functions have these properties.

4.4. Kernel Definition

Kernel function is to transform the lower dimension data into higher dimension data without computing mapping [5][36][39]. Every kernel has an associated feature mapping φ. This function φ takes input X and maps it into higher dimension plane F.

$$\varphi : X \rightarrow F$$

Note that every function cannot be a kernel function. Any function to be a kernel it must satisfy the Mercer's Condition.

Different Kernel Functions.

1. **Linear Kernel** [5]

The linear kernel function is the easiest function in compared with all kernel functions. It is calculated by performing inner dot product of two vectors x and xi and adding a free constant C [36][39]. Mathematical representation of this kernel function is shown below.

$$K(x, x_i) = x^T x_i + c \tag{4}$$

2. **Polynomial kernel** [5]

   The polynomial kernel function is non static kernel. Polynomial kernels are mainly used in the problems in which, all the training data is regularised [36].

   Mathematical representation of this kernel function is shown below

$$K(x, x_i) = (x^T x_i + 1)^d \tag{5}$$

Changeable factors in the polynomial kernel are degree d a constant term and slope alpha.

3. **Gaussian Kernel (RBF)** [5]**.**

$$K\ (x, x_i) = \exp\ \{\gamma\ (-\parallel x - x_i \parallel^2)\} \qquad \gamma \geq 0, \tag{6}$$

The Gaussian kernel is an example of radial basis function kernel. Gamma the regulating variable will is very important parameter in the Gaussian kernel. Gamma variable should be selected carefully. Small value may divert the classification and large value of gamma parameter lead to over fitting. [39] If the gamma parameter is selected large value the exponential curve will behave as linear

4. **Exponential Kernel**

Exponential kernel Representation on two sample is represented in the mathematical form is shown below.

$$k(x, x_i) = exp(-\frac{\|x - x_i\|}{2\sigma^2}) \tag{7}$$

Exponential kernel is same as Gaussian kernel. Only difference is there is no square term in the exponential kernel function. The variable parameter in the exponential kernel is gamma. Increasing gamma value will classify the new data accurately by decreasing the classification area.

4.5. Training of Support Vector machine.

In the previous chapter 3 we calculated the signal strengths at unidentified positions using the neural networks. The computed signal strength is to be classified in to two classes detectable or undetectable signal strength. For this we are taking the help of Support vector machines as it is discussed in the above subsections Support vector machine transforms the nonlinear data in to higher dimension using kernel functions and then then discover the best hyperplane that can separate the training data. The same discovered hyperplane is used for classification of new test data by this way Support Vector Machine will classify the testing data.

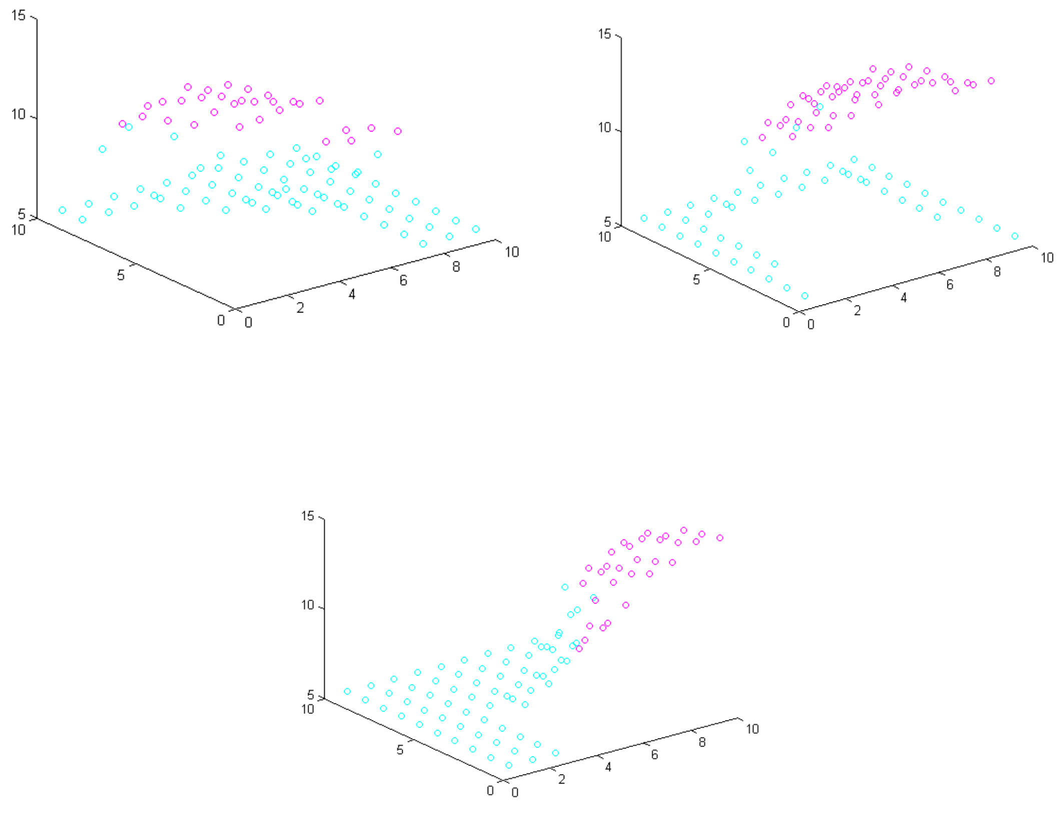

Figure 17: MATLAB result of classified signal strength in three cases

4.6. K fold Algorithm.

K fold cross validation is a process to calculate the accuracy of classifier. It is used to estimate the performance of classifier.

Operation of K fold algorithm.

Consider training data of *m* sets. K fold algorithm runs as follows. First arrange the training data randomly. After arranging data divide the training into k folds. Here we can take any value for K. If the last k fold set is not having same number of data sets as pervious folds leave as it is.

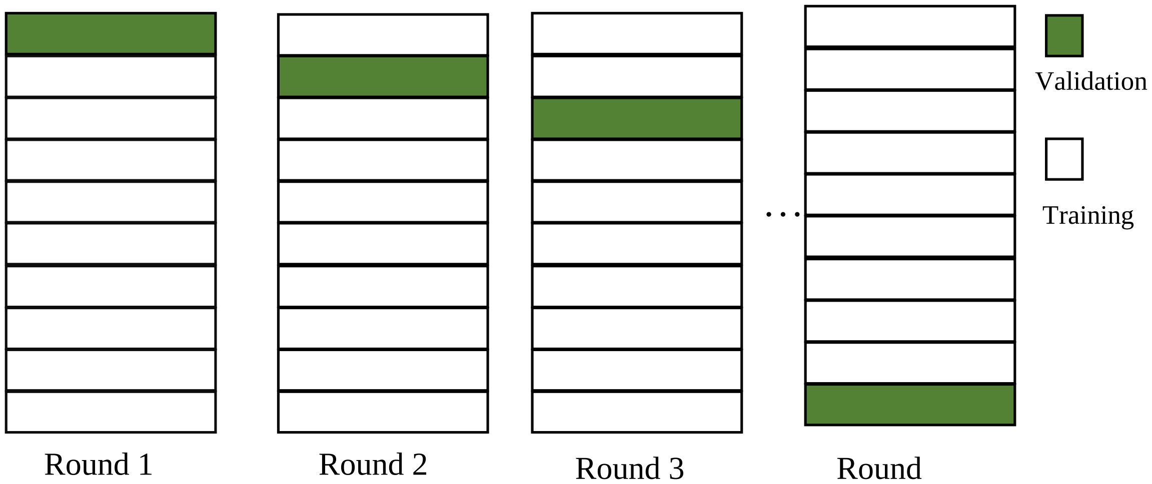

Figure 18: K fold algorithm

After dividing training data into K folds give each fold one number form $i=1, 2, 3 \ldots K$. Now train the classifier K times with all the training data that don't belong to fold *i*. Here training completes. Using this training classifier will classify the datasets in the fold *i*. After classifying the *i* fold data sets check for number of data sets that were wrongly classified and note it as n_i. Repeat the same procedure for all K folds and note down the values of n_i for $i=1, 2, 3 \ldots k$ folds.

Using the n_i values for all K folds we can estimate the classifier error.

$$\text{Classifier Error E} = \frac{\sum_{i=1}^{K} n_i}{m} \quad \text{where i= 1, 2, 3} \qquad (8)$$

To obtain the accurate results of classifier repeat the K fold algorithm several times and check the classifier error (E)

4.7. Cross Validation of SVM.

The classification accuracy is measured in terms of prediction accuracy. Prediction accuracy is the ratio of number of correctly classified data set to the total number of data set given to the SVM Classifier [19]. Cross validation is used to validate the predicted results [19]. In the previous section we are discovered the hyperplane that can separate the training data into different classes [21][25]. Now using the same hyperplane test data is classified. How accurately the new tested data is classified can be known from cross validation technique. In this project I am using the K fold cross validation technique for validating the data classified. In project three different cases of training data were considered with two different kernel functions. Those three data sets are classified and cross validated using k fold algorithm. Below are some of the tables that contains the cross validation results obtained using K fold algorithm.

Table 10: Prediction accuracy results of Case1 with RBF Kernel

	0.01	0.1	0.5	1	5	10	15
1	86.18%	86.12%	86.13%	86.11%	86.12%	86.11%	86.09%
10	86.04%	85.98%	85.99%	86.00%	85.98%	85.99%	86.00%
50	85.94%	85.89%	85.90%	85.90%	85.89%	85.88%	85.89%
100	85.83%	85.78%	85.78%	85.79%	85.78%	85.77%	85.76%
500	85.70%	85.65%	85.66%	85.67%	85.65%	85.64%	85.63%
1000	85.58%	85.52%	85.53%	85.54%	85.53%	85.52%	85.51%
2000	85.45%	85.40%	85.41%	85.42%	85.41%	85.40%	85.39%

Table 11: Prediction accuracy results of Case2 with Polynomial Kernel

	1	2	3	4	5
0.01	91.68%	91.72%	91.75%	91.79%	91.83%
0.1	91.86%	91.90%	91.93%	91.97%	92.00%
1	92.03%	92.07%	92.10%	92.13%	92.17%
10	92.20%	92.23%	92.26%	92.30%	92.33%
50	92.36%	92.39%	92.42%	92.45%	92.48%

Table 12: Prediction accuracy results of Case3 with polynomial Kernel

	1	2	3	4	5
0.01	97.04%	97.00%	96.97%	96.99%	97.00%
0.1	97.01%	97.03%	97.04%	97.05%	97.06%
1	97.08%	97.09%	97.10%	97.11%	97.13%
10	97.14%	97.11%	97.12%	97.13%	97.14%
50	97.15%	97.13%	97.14%	97.15%	97.16%

Above tables are the prediction accuracy calculated for three different cases with two different polynomial kernel functions. In the RBF kernel function the prediction accuracy are calculated by keeping sigma constant and varying box constraint value C. In table 10 rows are giving the prediction accuracy results by keeping C constant and varying sigma values and columns are giving results of keeping sigma constant and varying C.

Table 11 and Table 12 are the results of antenna placed at 5cm and 10cm respectively. In tables 11 and 12 the prediction accuracies are calculated by varying degree and box constraint parameters. Columns of the table are giving the prediction accuracies when degree kept constant. Column 1 gives the prediction accuracy when degree kept to 1. And rows are giving the results of cross validation when C kept constant and varying degree value. Comparing two tables 11 and 12 it can be known that prediction accuracy calculated in table 12 are somewhat high compared to results obtained in table 11. These are the prediction results obtained from classification of support vector machines. Now these results are compared with respect to other cases and predicted the best placement of RFID reader antenna and tag positon.

Initially we trained SVM classifier model with polynomial kernel and predicted the class of the new data. Using the cross validation technique prediction accuracy is calculated for different degree values d=1, 2,3,4,5 and keeping box constraint value C=50. Below is the prediction accuracy comparison table for three different cases.

Table 13 Prediction Accuracy of Polynomial kernels when C kept constant for different degree values

C	**50**	**50**	**50**	**50**	**50**
D	1	2	3	4	5
PA(Case 1)	94.81%	94.86%	94.78%	94.83%	94.84%
PA(case 2)	91.57%	91.82%	92.00%	92.13%	92.20%
PA(Case 3)	94.14%	94.23%	94.22%	94.21%	94.16%

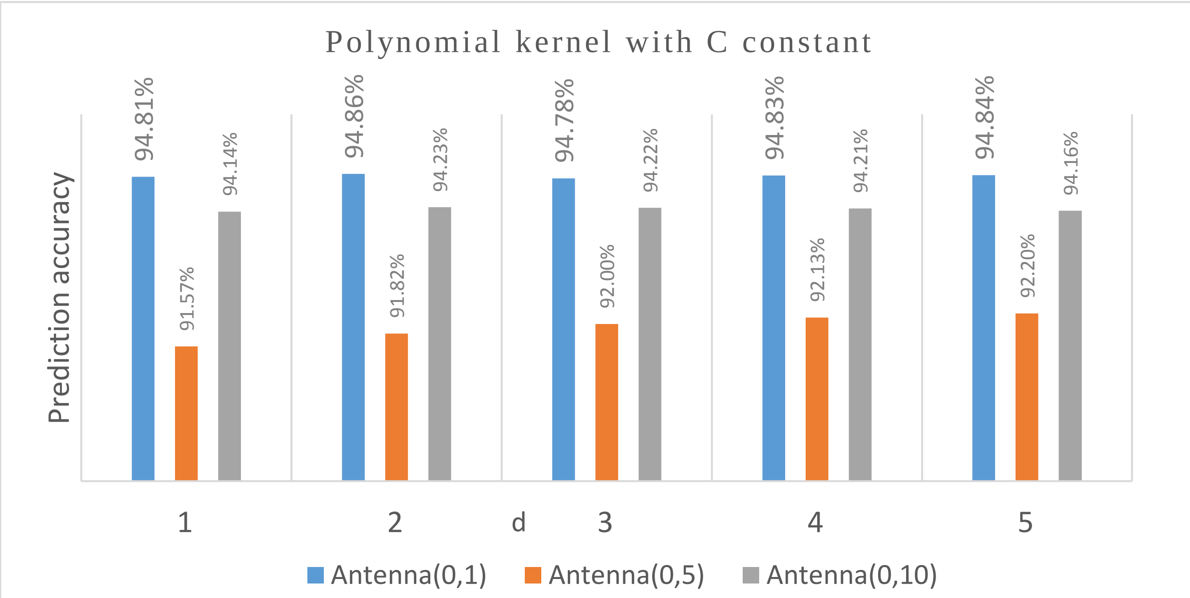

Figure 19: Polynomial kernel prediction accuracy for different d values with C const.

The prediction accuracy represented in the above graph is for comparison among the three cases. The accuracy of Prediction gives the performance of classifier. If we see the result bar graph given above it can be noted that for degree d=4 better results are achieved in all three cases than any other d value. [17]

In the second case of polynomial kernel we kept degree d=2 constant and altered the adjustment values C=0.01, 0.1,1, 10, 50. The graphs for d=4 with different C values is shown in Figure 20.

Table 14: Projection Accuracy of Polynomial kernels when d kept constant for distinct cases

d	**4**	**4**	**4**	**4**	**4**
C	0.01	0.1	1	10	50
PA(Case1)	92.50%	93.89%	94.36%	94.68%	94.83%
PA(Case2)	88.25%	88.78%	90.71%	91.63%	92.13%
PA(Case3)	95.00%	96.11%	96.86%	97.05%	97.13%

The results with C= 10, 50, are relatively giving good results when compared with all other cases.

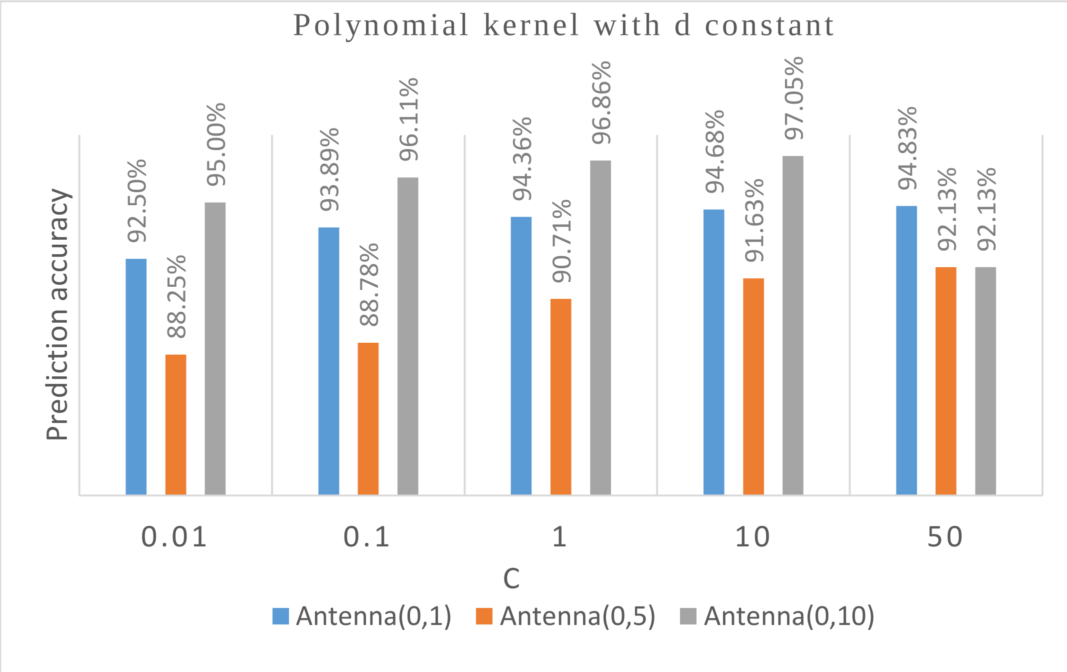

Figure 20: Polynomial kernel prediction accuracy for different d values with C const.

However the results are good here in this for all cases. We check the results with other kernel for comparing between the kernel functions. Which kernel function is giving the best results and which kernel is to be used based on the position of antenna are cleared out with this comparison.

In this section we use the RBF kernel function to predict the signal classification accuracy. In the similar way as polynomial kernel in first case we conduct the classification by keeping trade off value constant C=2000 and varying RBF kernel parameter γ =0.01, 0.1, 0.5, 1, 5, 10, 15 and respective prediction accuracies are calculated and tabulated.

Table 15: Prediction Accuracy of RBF kernels when C kept constant for different cases

C	**2000**	**2000**	**2000**	**2000**	**2000**	**2000**	**2000**
gamma	0.01	0.1	0.5	1	5	10	15
PA(Case 1)	86.14%	85.77%	85.96%	86.13%	86.34%	86.54%	86.73%
PA(Case 2)	80.37%	79.77%	80.09%	80.43%	80.79%	81.08%	81.31%
PA(Case 3)	89.09%	88.66%	88.89%	89.09%	89.21%	89.38%	89.51%

The comparison results with these parameters are shown in below graph. Comparing the results among three cases it is known that γ=10 and 15 are giving good results when compared with other γ values, this is considered as case 1 result of RBF kernel function.

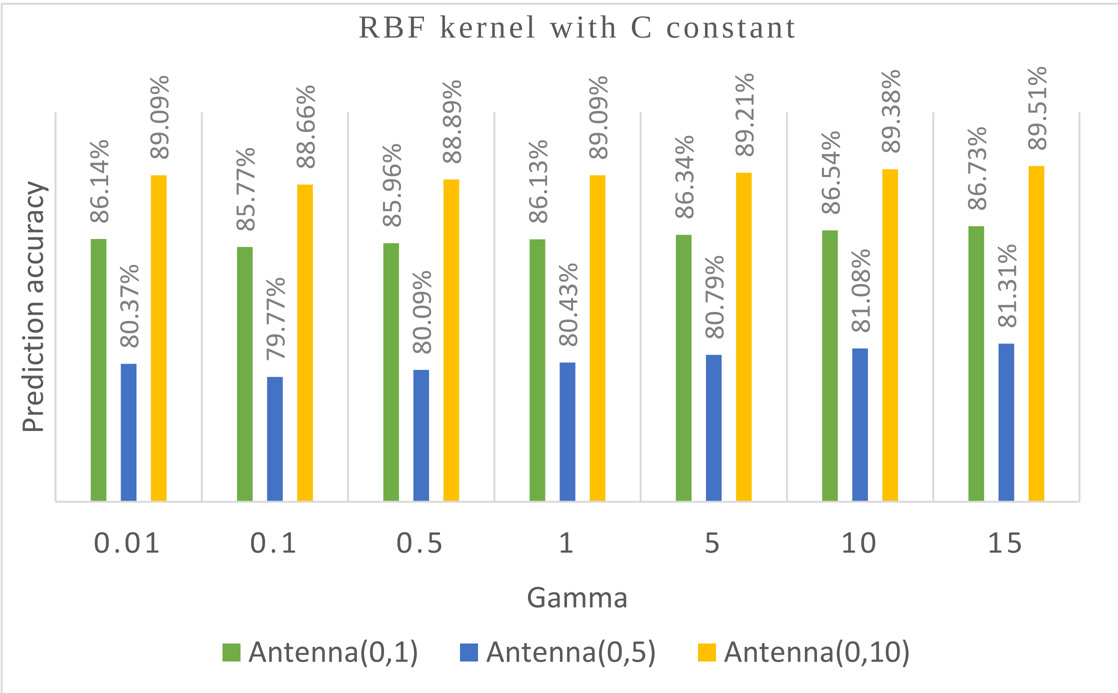

Figure 21: RBF kernel Prediction accuracy for different γ values with C const.

In the second case we kept γ=15 constant and varied the trade-off value C=1, 10, 50, 100, 500, 1000, 2000.

Table 16: Prediction Accuracy of RBF kernels when γ kept constant for different cases

gamma	15	15	15	15	15	15	15
c	**1**	**10**	**50**	**100**	**500**	**1000**	**2000**
PA(Case 1)	85.57%	85.79%	85.90%	86.07%	86.29%	86.52%	86.73%
PA(Case 2)	79.43%	79.57%	79.95%	80.29%	80.69%	81.00%	81.31%
PA(Case 3)	89.86%	89.86%	89.71%	89.68%	89.57%	89.55%	89.51%

Prediction accuracy results for different trade off values when taking γ=15 kept constant are shown in a bar graph. Increasing C values will improve the classification with loss of smoothness of the hyperplane.

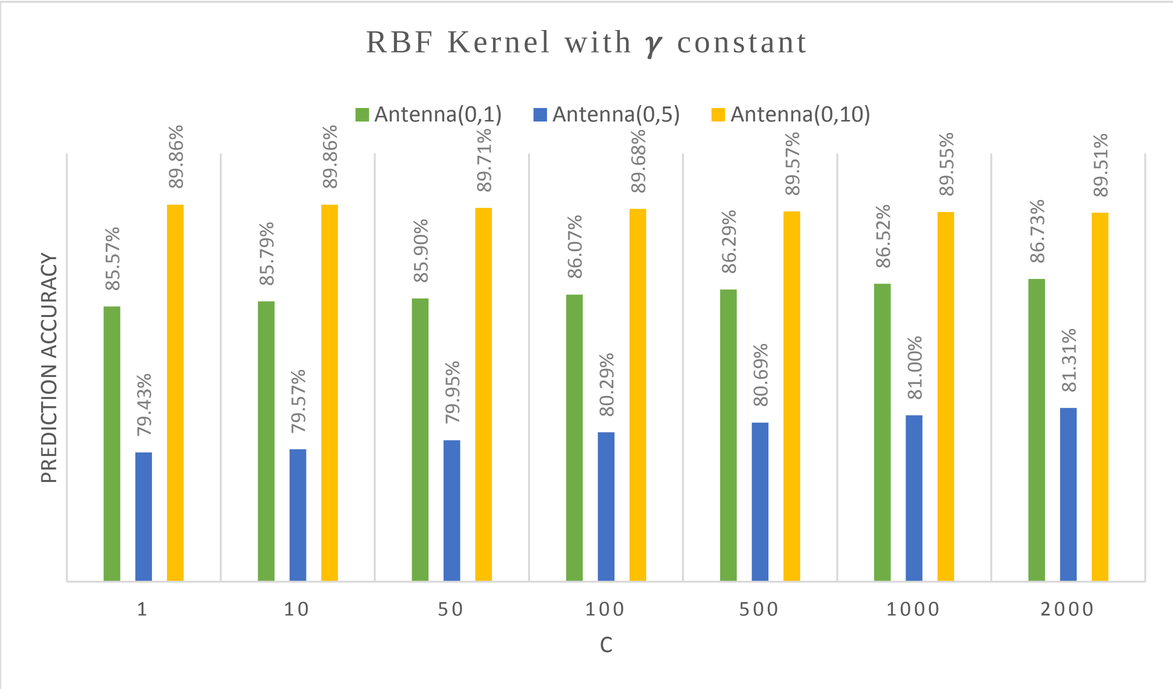

Figure 22: RBF kernel Prediction accuracy for distinct C values with fixed γ

It is observed form the bar graphs, and tables that case3 antenna at (0, 10) is giving good results when compare with the antenna positions. Prediction accuracy is more than 90% for RBF kernel functions. For real time applications more than 85% accuracy is needed [1]. If we observe the results it can be understood that there is no particular relation between kernel parameter, trade-off parameters and tag positions. So we conclude that while calculating prediction accuracy it is not needed to use predetermined kernel parameter values and trade-off constant [1]. Instead we can use different parameter values and find the results. To get best results it is better to go for trial and error method with all possible cases.

4.8. Conclusions

In this chapter small introduction about support vector machine was discussed and how support vector machine works to classify the data, what is linear classification and nonlinear classification are explained with Figures. Discovered signal strengths in the previous chapter at unidentified areas are classified using different kernel methods and they are cross validated using K fold cross validation technique. Cross validation results of the SVM classification for different kernels are given in the results sections in the form of tables for different cases using different kernel parameters and box constraint values. It is observed from the prediction accuracy tables that the tested data is classified almost 90% accurately.

CHAPTER 5

CONCLUSIONS AND FUTUREWORKS

5.1. Conclusions:

From these experiments it is concluded that position of RFID tag and the absolute location of the reader antenna will affect the reading ability of antenna. In this thesis I have analysed the factors effecting the tag signal based on results obtained by experiments. Performed an intelligent method using SVM for the prediction of RFID tag detectability. Depending on predicted tag detecting ability the finest tag position, reader position that maximise the tag detectability are found. Proposed method was verified for the RFID transponder on a 2D square box with 10cm × 10cm dimensions and the prediction results obtained are 85 to 93% accurate. Which is sufficient for successful tag detection [1]. By this way automatically RFID tag detection positions were found and increased the prediction accuracy.

5.2. Future works:

- In this project two methods are used, neural network for estimating signal strength and Support Vector Machine for classification using two methods is consuming so much money. Instead of using two methods further research is to made for implementing same project in single method.
- In the further researches Different environmental conditions will be considered while performing the experiments like doing the experiments with liquid containers and metals and in the areas where radio waves will move.
- Real time RFID antennas are placed at some height from ground. This factor was omitted in this research. In future researches the height factor will also be considered and performed the experiments as per the requirements.

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